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Prostate Disease Diagnosis from CT images using GA optimized SMRT based Texture Features

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Abstract

Nowadays prostate disease is very common in adult and elderly men. Since all types of prostate diseases are having similar symptoms, it is difficult to diagnose malignant prostate at an early stage. In this work an attempt is made to identify the types of prostate diseases from abdomen CT images of the patients using texture analysis. Prostate region is segmented from the CT image slice. Texture features are extracted from the segmented images using an evolving transform named Sequency based Mapped Real Transform (SMRT). Six different SMRT feature sets are derived by varying sub image size and block size. Each feature set is optimized using Genetic Algorithm (GA). The best feature set is selected based on classification accuracy. KNN classifier used. SMRT texture feature set with sub image size and block size 32 gives high classification accuracy.

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Keywords: Prostate diseases; Texture Features;SMRT;Genetic algorithm;KNN classifier

1. Introduction

Prostate cancer is one of the most diagnosed malignancies in men over the age of 60[2]. Thousands of men die due to this disease every year. Prostate cancer is curable in its early stages. But it doesn't show symptoms in early stages. Disease takes up to ten years to become life threatening. However, some prostate cancers can grow and spread quickly[1]. Educating men is important to understand the risk of progression and the various treatment options.

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Earlier stage diagnosis of prostate cancer is difficult because other prostate diseases also have similar symptoms. The other common prostate diseases are Benign Prostate Hyperplasia (BPH)[3] and Prostatis. BPH is a noncancerous enlargement of prostate gland. Prostatis is an inflammation or infection of prostate gland.

Prostate specific Antigen (PSA) screening and Digital Rectal Examination (DRE) are the methods available currently for the early stage detection of prostate cancer. PSA screening is not completely reliable since BPH and Prostatis can also cause an increase in PSA level. Also a 'normal' PSA does not completely rule out prostate cancer[3]. Though DRE is inexpensive and less time consuming to get the results, it detects the tumour only when it reaches a volume suggesting aggressive biological activity[3].

Generally, imaging techniques such as Magnetic Resonance Imaging (MRI) and Trans Rectal Ultra Sound (TRUS) imaging are suggested only if carcinoma is suspected. Even though TRUS guided biopsy provides correct diagnosis, it is painful and expensive. MRI, being expensive, is done to locate and quantify the carcinoma. Presently, CT images are used in cancer treatment for guiding radiotherapy[6], provided the cancer is in its early stage. Literature shows that research has been carried out in prostate diagnosis from TRUS images[4,5].

Large number of research efforts has been done in the field of analysing medical images. The aim of such researches is to assist in diagnosis and clinical studies[7]. It has also shown that texture analysis provides an effective tool in Medical image classification.

Texture is characterized by pixel patterns in an area around a pixel. This can be perceived in images as homogeneous visual patterns. Texture analysis consists of extracting parameters characterizing the arrangements of these visual patterns. A number of methods like statistical, structural and transform based methods have been developed for texture feature extraction since the advent of research in this field. Statistical methods commonly used are based on Haralick features derived from Gray Level Co-occurrence Method (GLCM)[8] and Gray Level Run length matrix(GLRL) based features[9]. Texture is also defined by texture primitives. Spatial organisation of texture primitives according to some placement rules to generate the complete pattern is used in structural approach. Features are obtained from these structural patterns[10]. Transform based methods use Fourier[11], Haar[12] and wavelet transforms[13] for extracting texture features.

Many of these feature extraction methods are used in medical image analysis. GLRL method has been used in brain tumour detection from CT images[14]. Wavelet based GLCM method is used in brain tumour[15] and lung cancer detection[16]. Textural feature extractions based on new transforms continue to evolve.

MRT (Mapped Real Transform, originally M-dimensional Real Transform) is an evolving transform for frequency domain analysis of signals using real additions alone[18]. The visual pattern[19] of MRT coefficients show that it can be used for texture analysis. 1-D and 2-D MRT texture features outperformed GLRL and GLCM methods in predicting the crushability of kidney stones[23].

One of the best imaging techniques to acquire images of soft tissues behind bone structures is Computed tomography (CT). Advantages of using CT include lower cost, short imaging time and widespread availability. A modern multislice CT machine enables the rapid acquisition of precise sets of successive images with very high resolution supporting a more confident diagnosis. The images have clear visualization of anatomical features and structures for the purpose of anatomical texture analysis.

The paper presents a non-invasive technique to identify prostate diseases from Abdomen CT image slices using transform based texture analysis. Transform used for analysis is 2-D Sequency based MRT which is explained in section 2. Section 3 briefs texture features based on 2-D SMRT. Feature subset selection using Genetic Algorithm (GA) is explained in section 4. K Nearest Neighbour (KNN) classifier explained in section 5 is used for image classification. Section 6 describes the collection of data and methods used. Results are tabulated and analysed in section 7. The work is concluded in section 8.

2. 2-D SMRT

Two Dimensional Discrete Fourier Transform (2-D DFT) computations was modified by projecting the data onto the N/2 twiddle factor axes, exploiting the periodicity and symmetry properties, and hence the complex multiplications were reduced from N^2 to N/2 per coefficient[17]. This restructured DFT computation was modified into an integer to integer transform, MRT, that involves only real additions rather than complex multiplications[18].

The data matrix, $X = [x(n_1, n_2)]$, $0 \le n_1, n_2 \le N-1$ is mapped to MRT coefficients, $Y_{k_1,k_2}^{(p)}$ by

$$Y_{k_1,k_2}^{(p)} = \sum_{\forall(n_1,n_2)|z=p} X_{n_1,n_2} - \sum_{\forall(n_1,n_2)|z=p+M} X_{n_1,n_2} \tag{1}$$

$$0 \le k_1, k_2 \le N-1 \text{ and } 0 \le p \le M-1,$$

where $M = \frac{N}{2}$, $z = ((n_1k_1 + n_2k_2))_N$, $z = ((n_1k_1 + n_2k_2))_N$, k_1, k_2 frequency indices and p, phase index.

Equation (1) maps an NxN data matrix into M redundant matrices of size NxN. Many of the MRT coefficients are same or sign reversed form of some other coefficients. Different methods were proposed to eliminate the redundancy in MRT representation and retain the N^2 unique MRT coefficients in the form of an NxN matrix[19,20].

Visual pattern of unique MRT coefficients were analysed and derived a sequency based placement entitled, Sequency based unique MRT (SMRT), for N a power of two[21]. In this NxN matrix, there are (3N-2) different frequencies (k_1,k_2 pairs) and the remaining are the phase terms[19]. Fig. 1 shows the index pattern k_1, k_2, p of the 64 unique MRT coefficients for N=8 in the SMRT matrix.

000	010	011	012	013	020	022	040
100	110	310	510	710	120	320	140
101	111	311	511	711	121	321	141
102	112	312	512	712	122	322	142
103	113	313	513	713	123	323	143
200	210	211	212	213	220	620	240
202	610	611	612	613	222	622	242
400	410	411	412	413	420	422	440

Fig. 1. Index Pattern of SMRT Coefficients for N=8

3. SMRT based Texture Features

SMRT based Texture features are derived by analyzing the visual pattern[22] of SMRT coefficients[23]. The pixel patterns of few SMRT coefficients in an 8 × 8 image matrix are shown in Fig.2. The '+' sign indicates addition and '-' sign denotes subtraction of the pixel value in the computation of SMRT coefficient. Blank cells indicate that they do not contribute to the SMRT coefficient.

+				-			
			-				+
		-				+	
	-				+		
-				+			
			+				-
		+				-	
	+				-		

k_1=1,k_2=1,p=0

	+		-		+		-
-		+		-		+	
	-		+		-		+
+		-		+		-	
	+		-		+		-
-		+		-		+	
	-		+		-		+
+		-		+		-	

k_1=6,k_2=2,p=2

+	-	+	-	+	-	+	-
+	-	+	-	+	-	+	-
+	-	+	-	+	-	+	-
+	-	+	-	+	-	+	-
+	-	+	-	+	-	+	-
+	-	+	-	+	-	+	-
+	-	+	-	+	-	+	-
+	-	+	-	+	-	+	-

k_1=0,k_2=4,p=0

Fig. 2. Visual pattern of MRT coefficients corresponding to three different k_1,k_2,p values

These visual patterns show that different SMRT coefficients represent texture patterns in different spatial distances. Hence texture features are derived corresponding to each frequency from the absolute sum of the phase terms for individual blocks. The features for the whole image are derived from the combination of respective frequency components of each block and is expressed as[23],

$$f_{k_1,k_2} = \frac{\sum_{i=1}^{N_b} \sum_p \left| Y_{k1,k2}^{(p)} \right|}{I \times I} \quad (2)$$

where IxI - size of image, NxN – size of image block and N_b- No. of blocks = I^2/N^2.

The SMRT placement in Fig .1 and eqn. (2) suggests that SMRT based texture feature calculation is simply the row wise or column wise addition of elements in SMRT matrix.

There will be 22 different k_1, k_2 pairs in SMRT matrix for N=8 and hence 22 texture features as in Table 1. In general, the number of texture features for an NxN data block, N a power of 2, will be (3N-2). Hence when N is 16 and 32, there will be 46 and 94 texture features respectively.

Table 1. SMRT Texture Features for N=8

Sl. No.	$f(k_1,k_2)$	k_1	k_2	p	Sl. No.	$f(k_1,k_2)$	k_1	k_2	p
1	$f(0,0)$	0	0	0	12	$f(1,2)$	1	2	0,1,2,3
2	$f(0,1)$	0	1	0,1,2,3	13	$f(2,1)$	2	1	0,1,2,3
3	$f(1,0)$	1	0	0,1,2,3	14	$f(3,2)$	3	2	0,1,2,3
4	$f(0,2)$	0	2	0,2	15	$f(6,1)$	6	1	0,1,2,3
5	$f(2,0)$	2	0	0,2	16	$f(1,4)$	1	4	0,1,2,3
6	$f(0,4)$	0	4	0	17	$f(4,1)$	4	1	0,1,2,3
7	$f(4,0)$	4	0	0,1,2,3	18	$f(2,2)$	2	2	0,2
8	$f(1,1)$	1	1	0,1,2,3	19	$f(6,2)$	6	2	0,2
9	$f(3,1)$	3	1	0,1,2,3	20	$f(2,4)$	2	4	0,2
10	$f(5,1)$	5	1	0,1,2,3	21	$f(4,2)$	4	2	0,2
11	$f(7,1)$	7	1	0,1,2,3	22	$f(4,4)$	4	4	0

4. Feature Subset selection using Genetic Algorithm

All possible combinations of the 22 features (N=8) i.e., $22C_1$ to $22C_{22}$, were considered to find feature subset that will give the highest classification rate in[23]. The combination that gives maximum classification with minimum number of features was selected as the optimal feature set. But as N increases, the number of features also increases and the procedure becomes tedious. Hence, genetic algorithm (GA) based optimization is performed to find features with maximum classification accuracy[25].

Number of variables in GA is taken as total number of texture features, n. An individual is encoded as n bit binary string. Each bit in the string corresponds to a feature with '1' indicating selection and '0', for omission of that feature. Hence each individual represents a feature subset. Genetic operators used in this optimization are Roulette wheel selection, single point crossover and mutation with a probability of 0.001.

5. KNN Classifier

KNN classifier is based on a simple non parametric algorithm. It's a lazy learning algorithm as it does not abstract any information from the training data during the learning process. The algorithm assumes data to be classified are points in a feature space. Hence they have a notion of distance. The unknown pattern is labeled into a class by the influence of K number of nearest neighbors. The neighbors are identified by a distance metric.

6. Material and Method

The study has been carried out on data acquired from 20 patients. Abdomen CT images and the supporting clinical details of persons validated by urologist are collected from hospital. Out of the 20 patients, seven are suffering from hard prostate, three have localised carcinoma, six have BPH (two with mild enlargement) and the remaining four are with normal prostate. Different slices of CT images are obtained from the acquired data. The prostate is manually segmented from the images under the guidance of an experienced urologist. Prostate located in the abdomen CT image is shown in Fig. 3.

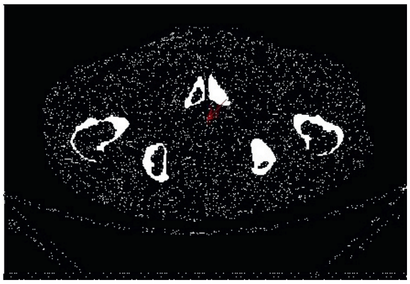

Fig. 3. Prostate in an Abdomen CT image slice

From the 20 CT data, 103 slices containing prostate area is obtained, out of which 68 slices are chosen as training set and the remaining 35 slices are used for testing the classifier. Fig. 4 shows Prostate diagnosis scheme.

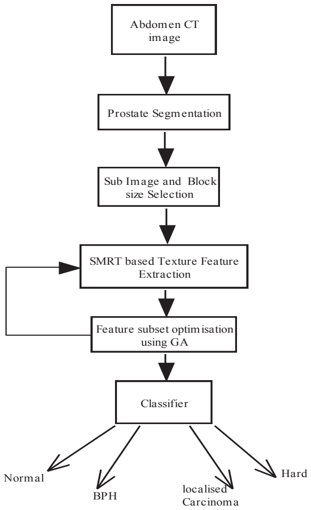

Fig. 4. Proposed Scheme

The prostate region is not exactly locatable from various slices of the CT image. Hence the experiment is performed for different sub image size. Different block sizes are also considered to include all possible texture variations in the feature set corresponding to a sub image. The sub image size I chosen in this experiment are 8,16 and 32. Each sub image is divided into blocks of size I, I/2 and I/4, with a minimum size of 8. All possible combinations of block size are used for deriving the feature set. Hence, six different feature sets are generated and each feature set is optimised using GA.

The images are to be classified into four categories, namely, Normal Prostate, Local Carcinoma prostate, Hard Prostate (Fully malignant) and Enlarged prostate(BPH), using KNN classifier.

7. Results

Table. 2 shows the results of the experimental study performed on 103 CT image slices for different sub image size and block size. Number of features in the GA optimized feature set, number of test images correctly classified and classification accuracy of each feature set are also given in the table. Feature set obtained by considering 32 x32 sub image taken as single block gives the highest classification accuracy and is chosen as the optimum feature set. Classification details of the test images using optimum feature set are given in Table 3. The table shows that all the images of malignant prostates are 100% correctly classified. All the normal prostates are also classified as normal. The only misclassification observed in this experiment is on the class BPH. Out of the ten images under BPH category 8 are classified as BPH and two are misclassified as normal. The test data set used under BPH category includes two mild enlargement images and they are the one classified as normal instead of BPH.

Table 2. Classification Accuracy of Feature Sets

Sl. No.	Sub image Size (I)	Block size(N)	Total No. of Features	No. of features in GA optimized subset	No. of Test Images Correctly Classified	Classification Accuracy (%)
1	8	8	22	5	23	65.71
2	16	8	22	5	26	74.3
3	32	8	22	7	27	77.14
4	16	16	46	15	29	82.87
5	32	16	46	17	31	88.57
6	32	32	94	26	33	94.3

Table 3. Test Image Classification using 32x32 SMRT Texture Feature Set

Sl. No.	Class of Images	No. of Images in Each class	No. of Images classified to each class
1	Normal	9	11
2	BPH	10	8
3	Localised CA	6	6
4	Hard	10	10

Literature shows a related work by S.S.Mohammed et.al. for prostate cancer diagnosis from TRUS images[26]. It uses Fourier transform based textural features and SVM classifier, performed on 108 prostate region images with 90 training images and 18 test images. They classified the images into malignant prostate or not with an accuracy of 94.4%.

The results presented in this paper shows potential in classifying all the malignant tissue with 100% accuracy and that from widely available and affordable CT images.

8. Conclusion

The paper presents prostate image classification into different categories based on GA optimized SMRT texture features. Experiment is performed on CT image data collected from 20 patients with different classes of prostate diseases. Prostate sub image is divided into blocks of different size, converted into SMRT features, applied GA to optimize these features and presented to KNN classifier. The results are found to be promising when the size is varied up to 32. Presently only 20 patients and 103 CT image slices are utilized for the experimental study. Classifier is trained with 68 samples and tested with 35. Even then only two out of 103 are misclassified, which is due to the closeness of the image. The proposed technique correctly classifies images with very small localized carcinoma. Definitely this will help to diagnose prostate disease and malignant prostate tissues at an early stage from the low cost abdomen CT.

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